Differential Impacts of Conservation Agriculture Technology Options on Household Income in Sub-Saharan Africa.

Citation:

Tambo, Justice A., Mockshell, Jonathan. (2018). Differential Impacts of Conservation Agriculture Technology Options on Household Income in Sub-Saharan Africa. Ecological Economics, 151: 95–105.

Publisher's DOI:

https://doi.org/10.1016/j.ecolecon.2018.05.005

Access through CIAT Research Online:

http://hdl.handle.net/10568/92824

Differential impacts of conservation agriculture technology options on household income in sub-Saharan Africa

Justice A. Tambo[a, b*] and Jonathan Mockshell[c, d]

[a]Centre for Agriculture and Biosciences International (CABI), Rue des Grillons 1, 2800 Delémont, Switzerland

[b]Center for Development Research (ZEF), University of Bonn, Genscherallee 3, 53113 Bonn, Germany

E-mail: j.tambo@cabi.org

[c]International Center for Tropical Agriculture (CIAT), Apartado Aereo 6713, Cali, Colombia

[d]German Development Institute (DIE), Tulpenfeld 6, 53113 Bonn, Germany

E-mail: j.mockshell@cgiar.org

Abstract

Conservation agriculture (CA), which consists of minimum soil disturbance, crop residue retention and crop rotation, is claimed to generate a number of agronomic, economic and environmental benefits. Recognising these potential benefits, CA is widely promoted in efforts towards sustainable agricultural intensification. However, there has been an intense debate about its suitability in smallholder farming environments, and this has stimulated a growing interest in the adoption and impacts of CA technologies in sub-Saharan Africa (SSA). Using survey data from maize-growing households in nine SSA countries, this paper seeks to add to the extant literature by examining the drivers and welfare impacts of individual and combined implementation of the three components of CA. We employ inverse-probability-weighting regression-adjustment and propensity score matching with multiple treatment estimators. Overall, results show that adoption of a CA technology significantly increases total household income and income per adult equivalent. Disaggregating the CA components, we find that adoption of the components in combination is associated with larger income gains than when the components are adopted in isolation, and the largest effect is achieved when households implement the three practices jointly. Nevertheless, implementation of the full CA package among the sampled households is very low, with an average adoption rate of 8%. We identify key factors that might spur increased adoption, including education, secure land rights, and access to institutional support services. Results further show that the determinants and impacts of the CA components vary considerably among the study countries, suggesting location specificity of CA. Our results are consistent across alternative estimators.

Keywords: Conservation agriculture; Sustainable intensification; Technology adoption; Household income; Sub-Saharan Africa

1. Introduction

Producing sufficient food to meet growing demand is an issue of great concern, particularly in sub-Saharan Africa (SSA) where agricultural productivity is very low and about 307 million people (31% of the population) are estimated to be severely food insecure (van Ittersum et al., 2016; FAO et al., 2017). Unfortunately, the challenges of climate change, land degradation, rapid population growth, urbanisation, exacerbate the situation (Godfray et al., 2010). Moreover, agriculture contributes to environmental problems through the emission of greenhouse gases and the degradation of natural resources. Thus, the increasing demand for food must be met while simultaneously mitigating environmental problems emanating from agriculture (Foley et al., 2011, Tittonell et al., 2016). This calls for sustainable agricultural intensification (SAI), that is, producing more food while conserving natural resources and the environment (The Montpellier Panel, 2013). In recent years, increasing attention has been paid to promoting SAI practices, and notable among them is conservation agriculture (CA).

CA combines profitable agricultural production with environmental conservation and sustainability through the simultaneous application of three principles, namely, minimum soil disturbance, permanent organic soil cover or crop residue retention, and crop rotation (FAO, 2017). Soil tillage has been associated with structural degradation of soil, which leads to soil erosion and a reduction in soil organic matter in the long term (Kassam et al., 2009). Conversely, the introduction of minimum soil disturbance, which involves shifting from the conventional plough-based farming systems to minimum or zero tillage, or seeding directly into untilled soil, may help to curb the negative impacts of soil tillage and to improve the quality of soil structure (Hobbs et al., 2008; Kassam et al., 2009). Permanent soil cover entails retaining the residues of planted crops on the farm all year round. It can also be achieved through cover cropping and green manuring. Among the advantages of this practice are the protection of the soil from the physical impact of rain and wind, the lowering of the soil temperature in the surface layers, the improvement of infiltration and retention of soil moisture, and the increase in the availability of plant nutrients (Jarecki and Lal, 2003). The third principle involves the rotation of cereals with legumes.

This practice increases plants nutrients, limits pest build-up (and thus decreases the need for pesticides), and enhances biodiversity (Kassam et al., 2009). Thus, beyond the agronomic benefits of crop yield improvement through increased organic matter, water conservation and improved soil structure, the sustained adoption of CA practices also generates environmental benefits, such as increased biodiversity, reduced soil erosion, improved water quality and increased soil carbon (FAO, 2017). Therefore, CA can play an essential role in sustainable intensification efforts.

However, despite the potential contribution of CA to sustainable food production, it has been a highly contested agricultural technology (Giller et al., 2009). There are diverse views on its potential impact by the many proponents and sceptics of the technology. While CA is associated with the aforementioned benefits, its adoption is hampered by several challenges, including the lack of mulch or competing uses for crop residues, the high cost of necessary farm equipment and labour constraints (Knowler and Bradshaw, 2007; Giller et al., 2009; Arslan et al., 2014). Based on its widespread adoption in the Americas and the increased challenges of soil degradation, labour shortage and poor productivity in SSA, CA is being increasingly promoted to SSA farmers by international research and development organisations (Andersson and Giller, 2012; Corbeels et al., 2014a). Considering the challenges involved in its adoption, however, there has been an intense debate about its suitability and impacts for African farmers, the majority of whom are smallholders (Giller et al., 2009; Andersson and D'Souza, 2014).

Consequently, there is a large and growing body of literature on the adoption and impact of CA. One strand of the literature has focused on using field experiments to assess the effect of the CA principles on crop yields, with mixed findings. For instance, Pittelkow et al. (2015) conducted a global meta-analysis of 610 field experiment-based studies and showed that conservation tillage reduces crop yields relative to conventional tillage, but the negative yield effects are minimised when conservation tillage is combined with the other two CA principles of residue retention and crop rotation. However, the study also stressed that under certain conditions, conservation tillage could generate equivalent or better yields than conventional tillage. Similarly, conducting meta-analysis of 41 CA experiments in SSA, Corbeels et al. (2014b) found that conservation tillage without mulch and/or crop rotation leads to a decrease in crop yields, but conservation tillage with mulching produces higher yields than conventional tillage, again suggesting the importance of combining the CA practices. The results of the numerous on-farm experiments, however, may not reflect the performance of CA under farmers' management conditions.

A second strand of the literature has examined the factors that influence farmers' adoption of CA practices (e.g., Mazvimavi and Twomlow, 2009; Arslan et al., 2014; Grabowski et al., 2016; Ngoma et al., 2015). In their review and synthesis of 31 such studies, Knowler and Bradshaw (2007) identified a plethora of variables that significantly affect adoption of CA, but noted that there are only a few variables that universally explain adoption across the various studies. Another strand includes more recent studies that analyse the implications of adoption of CA practices for crop productivity and household welfare (e.g., Nkala et al., 2011; Ngoma et al., 2015; Abdulai, 2016; Tsegaye et al., 2016; Mango et al., 2017; Ng'ombe et al., 2017). The findings have been relatively inconsistent across studies. For example, Nkala et al. (2011) found that CA technology adoption is significantly associated with higher crop productivity but not with household income and food security in Mozambique, while Abdulai (2016) showed that the adoption of CA technology significantly increases maize productivity and reduces household poverty in Zambia. Here, we contribute to the literature by analysing the impact of CA adoption options on household welfare using data from nine SSA countries. In particular, we aim to address three questions: (1) what factors influence the adoption of CA practices when adopted independently or jointly?; (2) what is the impact of the adoption of CA practices on household income?; and (3) does the adoption of CA practices in combination result in larger income gains than when adopted individually? To address these research questions, we employ the inverse-probability-weighted regression-adjustment (IPWRA) approach, which allows us to attenuate problems of selection bias. Additionally, propensity score matching (PSM) with multiple treatment estimations are conducted as robustness checks.

Our paper differs from previous studies in that we analyse the determinants and impacts of adoption of CA technologies individually and in combination. In order to realise the full benefits of CA, farmers are encouraged to adopt the complete package of minimum soil disturbance, residue retention and crop rotation (FAO, 2017). However, implementation of the full package is often challenging in resource-poor and smallholder environments, hence, partial adoption is very common (Mazvimavi and Twomlow, 2009; Arslan et al., 2014; Pittelkow et al., 2015). Thus, farmers may adopt a single practice or a combination of two practices or the full package. However, previous analyses of the determinants and impacts of CA have often overlooked these different adoption options. Most existing literature has either analysed a single CA practice or has aggregated the three CA practices by defining adopters as farmers who were practicing at least one of the CA principles. These approaches may obscure important information about the combination of CA practices. Recently, Ng'ombe et al. (2017) attempted to address this gap in the CA literature, but they only analysed the impact of CA adoption on crop revenue using data from Zambia. Implementation of the CA principles may result in resource reallocation that may indirectly affect household income, which is a more comprehensive measure of welfare.

The rest of this paper is structured as follows. Section 2 provides an overview of the data and estimation methods. Estimation results are presented and discussed in Section 3, and Section 4 concludes.

2. Methods

2.1 Data

Our analysis is based on a cross-sectional sample of 3,155 smallholder maize-producing households in over 100 villages in nine countries across SSA (see Figure 1). The study countries include Ghana and Nigeria (West Africa); Ethiopia, Kenya, Tanzania and Uganda (East Africa); and Malawi, Mozambique and Zambia (Southern Africa). The data was collected by the Africa and Intensification (*Afrint II*) project in 2008.[1] The Afrint II project adopted a multistage sampling technique, involving purposive sampling of countries, regions and villages, and random sampling of households. First, countries were purposively selected with respect to their production potential of four important staple food crops in

[1] The data is publicly available at the Afrint database: http://www.keg.lu.se/en/research/research-projects/current-research-projects/afrint. Accessed in August 2017.

SSA (maize, cassava, rice and sorghum). Regions within countries and then villages within regions were purposively selected based on their agricultural potential and agro-ecological differences. Finally, farm households were randomly drawn from the selected villages. Thus, the sample is not representative of the selected countries but captures a wide range of agro-ecological conditions and smallholder production systems across SSA. The survey focused on agricultural intensification, staple crop production, adoption of production technologies, land resources, commercialisation of major staple crops, institutional conditions, household income, and demographic and socioeconomic characteristics of households. A detailed description of the data and sampling strategy can be found in Djurfeldt et al. (2011).

Figure 1: Map showing the study countries. Points represent the survey regions, which include Bako, Yetmen, Bekoji and Assebot (Ethiopia); Eastern and Upper East (Ghana); Kakamega and Nyeri (Kenya); Ntchisi, Thiwi, Bwanje and Shire (Malawi); North, Centre and South (Mozambique); Kaduna and Osun (Nigeria); Kilombero and Iringa (Tanzania); Eastern, Central, South Western, North Western and West Nile (Uganda); and Mkushi and Mazabuka (Zambia).

2.2 Empirical strategy

As already described, CA involves three practices that may be adopted jointly or independently. Thus, adoption of a CA technology involves a choice among eight alternatives: (1) no adoption; (2) minimum soil disturbance (MSD) only; (3) residue retention (RR) only; (4) crop rotation (CR) only; (5) minimum soil disturbance and residue retention (MSD + RR) only; (6) minimum soil disturbance and crop rotation (MSD + CR) only; (7) residue retention and crop rotation (RR+CR) only; and (8) the complete package of minimum soil disturbance, crop residue retention and crop rotation (MSD + RR + CR). We view households' choice of CA practices from the perspective of a random utility framework, in which they choose a CA practice or combination of practices that maximise their utility by comparing it with the utility provided by other alternatives.

We analyse the impact of farmers' choice of the CA practices on household welfare. Our indicators of household welfare are household income and income per adult equivalent (AE). Household income comprises farm and non-farm income, whereas income per AE is total household income expressed in annual per adult equivalent basis.[2] There are a number of pathways through which adoption of a CA practice can affect household income. For instance, the agronomic benefits associated with CA, such as improved soil structure, increased organic matter, moderation of soil temperature and water conservation, could increase crop yields, which may subsequently increase household income through increased availability and sales of foodstuffs. Furthermore, CA may reduce production costs (e.g., pesticide, tractor, and fuel costs) and thus enhance household income. In addition, CA practices may save time and labour (especially in peak seasons) that can be reallocated to alternative income-generating activities, but on the other hand, it is possible that without the use of pesticides, CA may

[2] Income per AE is a better measure of household welfare than total household income (Deaton 1997). Consumption expenditure would have been a more appropriate measure of welfare, but unfortunately the survey data used in this study did not capture quantitative information on consumption expenditure. We use the OECD adult equivalent scale, which is computed as $1+0.7(A-1)+0.5C$, where A and C represent the number of adults and children in a household, respectively.

increase household labour requirements for weeding, and thus reduce household income (Giller et al. 2009; Arslan et al. 2013).

Adoption of CA practices is not randomly assigned, and farmers may decide whether to adopt or not depending on observed and unobservable characteristics. Thus, adopters of a CA package may differ in some systematic way from non-adopters, and the issue of self-selection may arise when estimating the impact of the adoption of CA practices. Moreover, unlike many studies on the impact of technology adoption that involve binary treatments, our analysis involves multiple treatment assignments (the aforementioned eight possible alternatives). This calls for estimation approaches that account for self-selection problems and multi-valued treatments. In impact assessment studies that rely on non-experimental cross-sectional design (as in our case), methods that are commonly employed to deal with selection bias problem include various instrumental variables (IV) and matching techniques. IV techniques require valid instruments for the endogenous treatment variables, which is particularly challenging in our case given the multi-valued treatments. Consequently, we employ two matching estimators: IPWRA and PSM with multiple treatments.

The IPWRA estimator models both the outcome and treatment to account for selection bias or non-random treatment assignment. It uses weighted regression coefficients to compute the treatment effect, where the weights are the estimated inverse probabilities of treatment (Wooldridge, 2010). Using the IPWRA approach to estimate the multivalued treatment effects of adoption of CA practices involves three steps (StataCorp, 2013).[3] First, the probability of adopting a CA practice (i.e., the treatment model) is estimated using multinomial logit regression, and the predicted probabilities are used in computing the inverse-probability weights. Literature on the adoption and impact of CA technologies (e.g., Knowler and Bradshaw, 2007; Arslan et al., 2014; Ng'ombe et al., 2017) helps determine which variables should be considered potential predictors. The variables include economic and demographic characteristics (e.g., age, gender and years of education of the household head, household size,

[3] This was estimated using the *teffects ipwra* command in Stata 14.

dependency ratio, farm size, livestock holding and asset index) as well as institutional and access-related variables (e.g., access to credit, extension services, and off-farm activities, membership in farmers' organisations and land tenure security). We also include regional dummies to account for regional heterogeneity. A detailed description of the variables included in the models is displayed in Table 1. Second, using these inverse-probability weights, weighted regression models of the outcome are fitted to obtain the expected outcomes of the probabilities of adoption and non-adoption of a CA practice. Finally, the mean outcomes for adopters and non-adopters are computed, and the difference between these two means provides the estimates of the treatment effects of adopting the CA practices. A key advantage of the IPWRA approach is its double-robust property, which allows the treatment effect to be consistently estimated as long as either the outcome model or the treatment model is correctly defined (Wooldridge, 2010).

The IPWRA approach is our preferred estimator, but we also use the PSM technique to assess the robustness of our findings. PSM is a method commonly used in the assessment of the treatment effects of projects or interventions. It involves matching the treated with a comparison group based on observable characteristics. Though it accounts for only observables, it is less restrictive as it is invariant to functional form assumptions. Following Lechner (2002), we apply the PSM with multiple treatments approach since our treatment variable (choice of CA packages) consists of eight alternatives. In the PSM with multiple treatments method, we estimate separate conditional probabilities between adopters and non-adopters of a CA technology to obtain propensity scores (i.e., probability of adopting a CA technology option) using logit regressions.[4] We then use the propensity scores to match adopters with non-adopters using kernel matching with a bandwidth of 0.06. Kernel matching involves using a weighted average of the non-adopters to construct the counterfactual (unobserved) outcome, and the weight is related to the distance on the propensity score between the adopters and non-adopters (Caliendo and Kopeinig, 2008). A further robustness check was performed using two other matching

[4] Alternatively, the propensity scores can be obtained using multinomial probit. Lechner (2002) found little difference in the relative performance of the two approaches.

algorithms: radius matching with a calliper of 0.05 and nearest-neighbour matching.[5] After ensuring that all covariates are balanced between adopters and non-adopters of the CA packages, we compute the treatment effects in the region of common support.

In both the IPWRA and PSM methods, we are interested in estimating the average treatment effect on the treated (ATT). The ATT estimates the expected average effects of adopting a CA technology option compared with the alternative of non-adoption of a CA technology, which is the base category. This can be expressed as:

$$
\begin{aligned}
ATT^{p_a \mid p_0} &= E\left\{Y^{p_a} - Y^{p_0} \mid C = P_a\right\} \\
&= E\left\{Y^{p_a} \mid C = P_a\right\} - E\left\{Y^{p_0} \mid C = P_a\right\}, \quad C \in \{1, 2.....8\}
\end{aligned}
$$

where P_a denotes adoption of a CA practice, and P_o indicates non-adoption of any of the CA technology options. Y^{Pa} and Y^{Po} represent the outcome (household income) for households that choose P_a and P_o respectively, and C indicates a CA adoption option, which ranges from 1 (no adoption) to 8 (adoption of the complete CA package).

3. Results and discussion

3.1 Descriptive statistics

A description of the variables included in the regression and their mean values are given in Table 1. We find that households in our sample are mostly poor smallholders with limited access to institutional support services. The average annual household income is 711 USD, while the annual per adult equivalent income is 180 USD. The majority (82%) of the households are headed by males, who are mostly middle-aged with very low levels of education. The average household consists of seven persons with a very high dependency ratio. The average farm size is about two hectares. The majority of the households are credit-constrained and only 29% of them have access to secure land tenure. About half

[5] Detailed information on propensity score matching as well as the different matching algorithms can be found in Caliendo and Kopeinig (2008).

of the households have access to agricultural extension services, while only 30% are members of farmer groups. Table 1 also depicts the average level of adoption of CA technologies. Overall, about 80% of the households have adopted at least one of the CA techniques. The most commonly practiced (24%) CA technique is CR singly. Among the combined CA practices, adoption of RR and CR jointly is the most common. While farmers are encouraged to adopt all three CA practices simultaneously to achieve maximum impact, only 8% of the households did so. This supports arguments that the combined adoption of all three CA components rarely occurs in any region of the world (Brown et al. 2017). The least practiced CA option is the combination of MSD and RR.

Table 1: Definition of variables in the regression

Variable	Description	Mean	SD
Outcome variables			
Household income	Total annual income earned by household in US dollars (USD)	710.94	990.66
Income per AE	Household annual income per adult equivalent in USD	180.37	375.55
Treatment variables			
MSD only	Household adopted only minimum soil disturbance (1=yes)	10.60	
RR only	Household adopted only residue retention (1=yes)	6.38	
CR only	Household adopted only crop rotation (1=yes)	23.91	
MSD + RR	Household adopted only minimum soil disturbance and residue retention (1=yes)	5.13	
MSD + CR	Household adopted only minimum soil disturbance and crop rotation (1=yes)	6.75	
RR + CR	Household adopted only residue retention and crop rotation (1=yes)	20.07	
MSD + RR + CR	Household adopted all the three CA practices (1=yes)	7.60	
Explanatory variables			
Age	Age of household head (years)	48.7	14.37
Gender	Gender of household head (1=male)	0.82	0.38
Household size	Household size (number)	7.10	4.39
Dependency ratio	Ratio of household members aged below 15 and above 61 to those aged 15-61	1.15	1.04
Education	Years of formal education of the farm manager	5.13	4.40
Farm size	Total cultivated area (hectares)	2.26	3.17
Livestock holding	Total livestock holding in Tropical Livestock Units (TLU)	1.63	3.18
Asset index	Household asset index	0.01	1.88
Off-farm activity	Household engages in off-farm income-generating activities (1=yes)	0.38	0.49
Credit access	Access to farm input credit (1=yes)	0.15	0.36
Land security	Household holds a formal title or registration of cultivated land (1=yes)	0.29	0.45
Extension access	Contact with extension agents (1=yes)	0.52	0.5
Group membership	Member of farmer group (1=yes)	0.30	0.46

Table 2 reveals interesting heterogeneity in uptake of CA practices across the study countries. Adoption of CR singly is very common in Ethiopia as nearly 60% of the households practiced only this technique. In Ghana, MSD options appear to be highly relevant as about 36% of the households adopted only MSD, while 19% and 16% of them combined MSD with RR and MSD with CR, respectively. Adoption of RR+CR is the most preferred option for the households in Kenya, Malawi and Uganda, particularly in Uganda where about 65% of the households have adopted this package. Non-adoption of CA is more common in Mozambique and Nigeria, with 48% and 34% of the sampled households, respectively, not adopting any of the CA practices. Implementation of a comprehensive CA package consisting of all the three practices is very low in most of the study countries, with even zero adoption in Mozambique. Tanzania shows the highest (17%) rate of adoption of the complete package (MSD+RR+CR).

Table 2: Adoption of CA practices in the sample countries

	No adoption	MSD	RR	CR	MSD+RR	MSD+CR	RR+CR	MSD+RR+CR
Ethiopia	11.74	0.00	6.05	59.43	0.00	0.71	21.71	0.36
Ghana	13.82	36.04	3.52	3.52	18.70	15.99	2.17	6.23
Kenya	14.67	0.33	18.33	3.67	1.00	0.00	45.67	16.33
Malawi	14.97	9.39	6.60	21.57	4.31	5.33	31.73	6.09
Mozambique	47.67	19.48	6.69	20.93	2.33	2.91	0.00	0.00
Nigeria	33.50	4.68	7.03	37.70	2.34	3.04	4.92	6.79
Tanzania	23.23	21.25	3.97	8.78	14.45	6.23	5.38	16.71
Uganda	4.40	0.00	6.58	22.88	0.31	0.31	64.89	0.63
Zambia	8.74	1.46	1.21	36.89	1.21	21.36	15.53	13.59

Table 3 presents the average household income earned by adopters of the various CA technology options. The results show that adopters of combinations of CA practices earned higher incomes (in terms of both total household income and income per AE) than non-adopters. Regarding the adoption of CA practices in isolation, there are statistically significant differences between adopters and non-adopters only in terms of income per AE. The statistically significant differences in average incomes seem to suggest that relative to non-adopters of a CA technology, adopters of combinations of CA practices achieve higher incomes than adopters of single CA practices. However, these are only mean comparisons and cannot be interpreted as impact of adoption of various CA practices. Such deductions can be made from the ensuing econometric analysis.

Table 3: Summary statistics of the outcome variables

	Household income		Income per AE	
	Mean[a]	SD	Mean[b]	SD
MSD only	546.54	619.55	168.39***	215.47
RR only	593.84	699.48	152.10***	155.43
CR only	588.79	818.95	122.44	168.82

MSD + RR	623.11	708.71	191.34***	293.50
MSD + CR	856.67***	992.31	201.89***	251.21
RR + CR	883.34***	1268.81	233.11***	369.00
MSD + RR + CR	1268.79***	1583.52	396.72***	1037.27

[a] Compared with income (mean=563.35; SD=723.94) of non-adopters of a CA technique.

[b] Compared with income per AE (mean=118.51; SD=134.44) of non-adopters of a CA technique.

*** denotes 1% statistical significance level.

3.2 Econometric results

As mentioned earlier, we assess the impact of adoption of CA techniques on household income using the IPWRA and PSM methods. We first estimate the determinants of adoption of the CA technologies. Afterwards, we present a disaggregated analysis of the impacts of adoption of CA technologies individually and in combination.

3.2.1 Factors influencing uptake of CA packages

Table 4 displays the parameter estimates of multinomial logit model, which is used to predict the treatment status (choice of CA practices) of the IPWRA estimator. The model thus shows the factors that influence farmers' choice of alternative CA practices. As expected, the results show some discernible differences in how the covariates affect the adoption of CA technology options. In contrast to previous studies (e.g., Ng'ombe et al. 2017), we find that the age and gender of the household head do not significantly affect the adoption of any of the alternative CA practices, suggesting that both male and female farmers as well as young and older farmers are equally likely to implement CA techniques, whether in combination or in isolation. The household size variable is strongly and significantly negatively related to the adoption of almost all the CA alternatives, which implies that households with fewer members are more likely to adopt CA technologies. CA is argued to reduce households' labour burden; hence, households with fewer members, and who are thus more likely to be labour-constrained, have a higher likelihood of adopting CA techniques. Moreover, the results show that the probability of adopting RR singly or RR in combination with CR increases with a higher dependency ratio, perhaps because households who have higher dependency ratio are less likely to have labour-active members. This further suggests that the potential labour-saving property of CA is essential for increased uptake.

We find that higher education levels of farm managers are positively and significantly related to the adoption of three CA packages, namely MSD+CR, RR+CR and MSD+RR+CR. Thus, higher literacy skills are essential in the adoption of CA practices in combination, but not in isolation. This is probably because combining CA practices is more knowledge-intensive than implementing them singly, and educated farmers may possess greater technical knowledge and skills to be able to practice CA packages. Farm size has a varied effect on uptake of the CA practice alternatives. Large farm size significantly decreases the probability of adopting RR singly or in combination with CR (i.e., RR+CR), and conversely, large farm size increases the likelihood of adopting CR only and MSD+CR. A plausible explanation is that households with large farm sizes may require large quantities of crop residues to practice RR, while large farm sizes allow households to rotate their crops on different plots. With the exception of adoption of MSD singly, adoption of all the alternative CA practices significantly increases with higher livestock holdings. This is partially consistent with Ng'ombe et al's (2017) findings, which indicated that livestock holding is positively related to the adoption of MSD singly and MSD+RR, but is negatively related to the adoption of MSD+CR and RR+CR. Results also show that asset-rich households are more likely to adopt all the three CA practices jointly. They also have a higher probability of adopting MSD and RR individually or in combination, but they are less likely to opt for CR in isolation or jointly with MSD. Households that engage in off-farm income generating activities are less likely to practice all the CA techniques jointly or to adopt the MSD+CR package and CR singly, but are more likely to adopt RR+CR. Access to credit, which helps to relieve households' liquidity constraints, is significantly associated with investment in a combination of all three CA techniques. Additionally, access to credit fosters the uptake of other CA packages, such as RR+CR and MSD+CR.

Table 4: Parameter estimates for factors influencing adoption of CA packages

	MSD only	RR only	CR only	MSD+RR	MSD+CR	RR+CR	MSD+RR+CR
Age	0.008	0.006	-0.004	-0.010	0.007	-0.005	-0.002
	(0.006)	(0.006)	(0.005)	(0.007)	(0.007)	(0.005)	(0.007)
Gender	-0.132	-0.039	0.218	0.283	-0.190	-0.097	-0.145
	(0.199)	(0.233)	(0.167)	(0.292)	(0.240)	(0.169)	(0.250)
Household size	-0.123***	-0.079***	-0.012	-0.102***	-0.070***	-0.103***	-0.094***

	(0.029)	(0.022)	(0.015)	(0.029)	(0.021)	(0.017)	(0.022)
Dependency ratio	-0.159	0.185**	0.047	0.007	0.094	0.236***	0.035
	(0.115)	(0.080)	(0.062)	(0.129)	(0.101)	(0.060)	(0.103)
Education	0.027	0.023	-0.005	-0.002	0.110***	0.062***	0.048**
	(0.020)	(0.020)	(0.017)	(0.029)	(0.024)	(0.017)	(0.023)
Farm size	-0.006	-0.147**	0.046*	-0.008	0.052*	-0.107*	0.021
	(0.029)	(0.067)	(0.025)	(0.028)	(0.028)	(0.058)	(0.031)
Livestock holding	0.091	0.105**	0.125***	0.167***	0.149***	0.183***	0.196***
	(0.058)	(0.041)	(0.031)	(0.038)	(0.036)	(0.032)	(0.036)
Asset index	0.142***	0.154***	-0.148***	0.138*	-0.093*	-0.020	0.137**
	(0.053)	(0.053)	(0.045)	(0.072)	(0.056)	(0.043)	(0.053)
Off-farm activity	0.159	0.218	-0.245*	0.153	-0.744***	0.601***	-0.500**
	(0.163)	(0.186)	(0.138)	(0.215)	(0.223)	(0.137)	(0.217)
Credit access	-0.184	0.261	0.785***	0.420	0.481*	0.831***	1.230***
	(0.368)	(0.344)	(0.222)	(0.350)	(0.288)	(0.230)	(0.255)
Land security	-1.085***	0.387*	0.993***	0.034	0.304	0.864***	0.460**
	(0.282)	(0.214)	(0.149)	(0.270)	(0.211)	(0.154)	(0.206)
Extension access	0.274*	0.502***	0.174	0.338	1.049***	0.399***	0.457**
	(0.164)	(0.181)	(0.130)	(0.219)	(0.200)	(0.138)	(0.200)
Group membership	-0.375	0.189	0.602***	0.444	1.275***	0.780***	1.286***
	(0.231)	(0.230)	(0.165)	(0.271)	(0.205)	(0.163)	(0.211)
Region fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	-0.161	-1.337***	-0.477	-1.060	-2.707***	-0.464	-1.691***
	(0.408)	(0.483)	(0.331)	(0.574)	(0.495)	(0.339)	(0.482)

***, **, * denote 1%, 5%, and 10% significance level, respectively

Results further show that households with secure land tenure are significantly more inclined to implement the complete CA package and to adopt CR and RR, either in combination or in isolation. This is consistent with previous studies (e.g., Gebremedhin and Swinton, 2003) that found that households with secure land tenure rights are more likely to invest in soil conservation techniques. Contact with extension agents, who are one of the key sources of information about agricultural technologies in SSA, significantly enhances the uptake of MSD+CR, RR+CR and MSD+RR+CR as well as the adoption of MSD or RR in isolation. Finally, households with members in farmer organisations (a proxy for social capital) have a higher probability of adopting most of the CA options, particularly combinations of the practices. This is resonates with Knowler and Bradshaw's (2007) observation that social capital is an important factor that universally explains the adoption of CA across previous studies.

3.2.2 Impacts of adoption of CA packages

Table 5 displays the results of the doubly robust IPWRA estimator on the impacts of alternative CA practices. To confirm the robustness of our ATT estimates, we also present results from applying three PSM techniques. The covariate balancing tests presented in Table A1 in the appendix show successful bias reductions after matching, while overlaps in the distribution of the propensity scores (see Figure A1 in the appendix) suggest a satisfaction of the common support conditions, using the kernel matching method. Our results are mostly consistent, regardless of the estimation technique employed. We find that adoption of CA practices in combination is strongly associated with increased household income than adoption of CA practices in isolation. The IPWRA estimates, for instance, indicate that the joint adoption of all three CA techniques improves total household income and income per AE by 537 USD and 228 USD, respectively. Similarly, the kernel matching estimates show that combining the three techniques enhances total household income and income per AE by about 500 USD and 166 USD, respectively.

The results further demonstrate that compared with non-adopters of CA technologies, adopters of MSD+CR earn about 261 USD and 64 USD more household income and income per AE, respectively, while adopters of RR+CR improve their household income and income per AE by about 219 USD and 59 USD, respectively. However, combining MSD with RR is significantly associated with an increase in only income per AE. Specifically, households that adopt MSD+CR obtained 76 USD extra income per AE relative to non-adopters of CA practices. The magnitudes of the ATT estimates indicate that the impact of a joint adoption of the three CA practices are larger than the sum of the impacts of adopting a package consisting of two CA practices, such as MSD+RR or MSD+CR. Interestingly, our results show that adoption of the CA practices in isolation (i.e., MSD only, RR only or CR only) yields low ATT estimates, which are mostly statistically insignificant. In particular, adoption of each of the three practices in isolation does not significantly enhance total household income. In terms of income per AE, only MSD appears to consistently generate positive impacts, producing a range of ATT estimates from 26 USD to 28 USD.

Overall, the results suggest that combining the CA practices is worthwhile in terms of enhancing household income, and the largest effect size is achieved when households implement the three practices jointly. Our findings are consistent with those of Ng'ombe et al. (2017) who found that combinations of CA practices yield higher crop revenue than uptake of the practices in isolation. However, they found that MSD+RR generates the highest crop revenue, whereas MSD+RR+CR produces the largest income effect in our case. Our findings are also in agreement with recent studies by Teklewold et al. (2013) and Wainaina et al. (2017) that have reported that sustainable agricultural practices provide larger income gains when adopted in combination rather than in isolation.

Table 5: Differential impacts of CA technology options

	IPWRA		Kernel matching		Nearest neighbour		Radius matching	
	Income	Income_AE	Income	Income_AE	Income	Income_AE	Income	Income_AE
MSD only	37.56	27.70*	22.53	25.74*	20.99	20.47	22.53	25.74*
	(45.16)	(15.02)	(58.41)	(15.94)	70.09	19.72	(58.41)	(15.94)
RR only	52.16	40.00	18.12	15.47	56.47	31.69*	18.12	15.47
	(61.56)	(25.84)	(66.42)	(17.2)	79.27	19.83	(66.42)	(17.20)
CR only	34.53	18.66	-47.01	0.27	-4.59	8.95	-51.88	-0.76
	(55.15)	(21.76)	(55.18)	(10.49)	66.71	12.75	(57.10)	(10.83)
MSD+RR	69.61	76.13*	89.02	63.64**	-2.30	43.39	89.02	63.64**
	(84.32)	(42.41)	(84.3)	(30.89)	106.72	35.01	(84.30)	(30.89)
MSD+CR	261.39**	63.84***	82.71	51.55**	5.13	60.39**	82.71	51.55**
	(129.48)	(24.54)	100.98	(23.5)	123.07	24.12	(100.98)	(23.50)
RR+CR	219.23**	58.70***	327.63***	89.50***	328.13***	87.33***	327.63***	89.50***
	(94.38)	(22.33)	(71.28)	(17.2)	77.70	19.42	(71.28)	(17.20)
MSD+RR+CR	537.09***	227.72***	499.41***	166.10***	533.99***	171.25***	499.41***	166.10***
	(139.09)	(60.05)	(148.21)	(43.05)	165.90	46.55	(148.21)	(43.05)

***, **, * denote 1%, 5%, and 10% significance level, respectively. All values are in USD. Values in parentheses are standard errors.

We also attempt to assess the differential impacts of the CA practices for the countries in our sample. The results of the IPWRA and PSM (kernel matching) estimations are presented in Tables 6 and 7, respectively. For the country samples, we are not able to compute estimates of the ATT for some of the CA packages due to the limited number of adopters of these packages, or dropping of observations that are not in the regions of common support. Thus, we report ATT estimates for CA packages for which we successfully match adopters with non-adopters of similar propensity scores within each country sample. Focusing on the IPWRA estimates, we find that households in Ghana and Tanzania increase their income through the adoption of all three CA techniques jointly. In Ghana, for instance, adoption of the CA package of MSD+RR+CR is significantly associated with an increase in household income and income per AE by 1231 USD and 318 USD, respectively. The results further show practicing MSD and RR together is significantly related to higher income in Ghana and Malawi, while adoption of MSD+CR enhances household income in Ghana and Tanzania. In Kenya, the CA package that significantly enhances household income is RR+CR. Adoption of MSD and CR in isolation are associated with significant improvement in household income only in Ghana, while applying RR singly enhances income only in Malawi.

The ATT estimates from kernel matching indicate that apart from Ghana and Tanzania, households in Nigeria also significantly improve their income by adopting the MSD+RR+CR package. With the kernel matching method, we are also able to obtain ATT estimates for adoption of some of the CA packages in Uganda and Zambia. Results indicate that relative to non-adoption of a CA technology, combining RR and CR results in a significant increase in household income in Uganda, but it worsens household income among the sample from Zambia. Overall, we find that the impacts of the CA packages vary considerably among the study countries. Moreover, in most cases, the effect sizes differ substantially between the two estimation methods employed, and this could be due to small sample size problems. The country-specific results could also be related to adaptation of the three CA principles to local contexts. Our analysis of the impacts of CA is based on the three recommended principles by the FAO (2017), without taking into account context-specific adaptations. However, studies (such as Ndah et al. 2014; Brown et al. 2017) have shown that there are differences in how CA is actually implemented on the ground across different regions in SSA. For instance, in Zambia, CA is promoted as Conservation Farming and consists of other practices beyond the three components considered in this study (Arslan et al. 2015). Consequently, the results in Tables 6 and 7 need to be interpreted with caution, and further research involving large country-level data as well as consideration of local modifications will be necessary to confirm our country-level results.

4. Conclusions

In an effort to achieve food and nutrition security while conserving natural resources and reducing environmental impacts, promotion of sustainable intensification practices has increased. One such approach is CA, which consists of three principles ─ minimum soil disturbance, crop residue retention and crop rotation. CA has been claimed to provide a number of benefits, including increased organic matter, water conservation, improved soil structure, reduced labour costs, increased yields, increased biodiversity, reduced soil erosion, and carbon sequestration. In order to realise the full benefits of CA, farmers are urged to combine the three CA principles. However, full implementation of the CA components is often challenging in resource-poor and smallholder farming systems, leading to debates about its suitability and impacts for African smallholders. Using survey data from 3,155 smallholder maize-growing households in nine SSA countries and matching estimators for treatment effects, this paper examines the determinants and income effects of individual and combined implementation of the three principles of CA. With this multi-country empirical analysis, we contribute to previous research works on determinants and impacts of CA practices as they have mostly neglected partial adoption as well as complementarities of the CA practices.

Results show that adoption of CA practices in combination is more strongly associated with increased household income than adoption of CA practices in isolation. In fact, adoption of the CA practices in isolation yields low income gains, which are mostly statistically insignificant. Overall, the results suggest that combining the CA practices is worthwhile in terms of enhancing household income, and the largest effect size is achieved when households implement the three practices jointly. In particular, we find that the impact of a joint adoption of the three CA practices is larger than the sum of the impacts of adopting a package consisting of two CA practices. The results also suggest that only about 8% of the sampled households have implemented a comprehensive CA package consisting of all the three practices, with almost zero adoption in three of the country samples.

Considering that CA practices can enhance household income while contributing to the reduction of greenhouse gas emissions from agriculture, adoption rates need to be improved. As the combination of CA practices are knowledge intensive, farmer to farmer knowledge platforms, effective extension service delivery systems and deployment of technological applications backed by subject matter specialists will be effective to up- and out-scale the adoption of CA. Moreover, without effective institutional and legal reforms to provide secured land tenure to farmers and increase access to credit, the rate of adoption of CA practices will remain slow. Finally, due to differences in institutional set-up and farming conditions, it is vital to consider location specificity of CA technologies; hence, promotion of the CA practices needs to be tailored to local conditions.

Our study has some limitations. First, we relied on cross sectional data, which does not allow analysis of dynamics of adoption of CA practices. Future research involving panel data will help to address this limitation and to properly account for potential bias from unobserved heterogeneity. Additionally, we could only analyse the impact of a few of the CA adoption options in the country samples due to limited observations. Moreover, we restricted our definition of CA to the three principles recommended by the Food and Agricultural Organization (FAO), without accounting for adaptation to local contexts. Thus, a more comprehensive country-level data is needed in follow-up studies.

Acknowledgements

This research was financially supported by the German Federal Ministry for Economic Cooperation and Development (BMZ) through the research projects “Promoting Food Security in Rural Sub-Saharan Africa: The Role of Agricultural Intensification, Social Security and Results-Oriented Approaches” and “Program of Accompanying Research for Agricultural Innovation (PARI)”. This article draws on data from the Lund University led Afrint II project, which was funded by the Swedish International Development Cooperation Agency and the Swedish Research Foundation. The authors gratefully acknowledge the team of researchers from Sweden and the nine African countries who were involved in the Afrint II project.

Table 6: IPWRA estimates of impacts of CA technology options in the study countries

		MSD only		RR only		CR only		MSD+RR		MSD+CR		RR+CR		MSD+RR+CR	
	Outcome	ATT	SE	ATT	SE	ATT	SE	ATT	SE	ATT	SE	ATT	SE	ATT	SE
Ethiopia	Income			109.21	98.71	72.90	47.77					20.57	47.01		
	Income_AE			25.46	28.24	17.84	11.97					9.26	11.53		
Ghana	Income	258.44***	76.88	-56.51	52.26	1055.25***	212.83	350.55***	124.45	734.66***	191.01			1231.14***	186.47
	Income_AE	102.95***	26.35	-39.70***	10.29	262.44***	52.01	193.27***	70.18	177.96***	42.28			318.47***	44.00
Kenya	Income			21.67	128.39	656.07	660.41					399.52**	183.79	170.76	397.14
	Income_AE			-3.73	27.68	94.75	88.65					90.34**	40.56	-60.77	182.24
Malawi	Income	18.51	33.06	992.35**	484.42	19.06	43.81	164.89**	80.35	1.94	64.93	63.25	45.07	11.87	40.75
	Income_AE	-7.67	13.08	575.22**	254.33	-9.82	14.22	57.59*	33.72	-13.91	18.09	1.69	11.71	-7.70	13.20
Mozambique	Income	57.49	86.03	84.30	252.33	-119.56	74.37								
	Income_AE	28.66	21.45	51.77	63.97	-16.93	13.63								
Nigeria	Income			393.19	247.94	-193.51	177.52							825.51	1730.65
	Income_AE			98.70	76.77	-54.86	50.05							266.49	348.92
Tanzania	Income	86.09	93.63	131.66	97.18	-2.64	140.37	203.91	129.74	182.36*	102.75	358.50	240.05	272.07**	134.02
	Income _AE	22.89	31.60	45.90	25.42*	37.29	57.67	34.14	41.67	71.88**	30.91	101.13*	55.33	99.24**	46.78

***, **, * denote 1%, 5%, and 10% significance level, respectively. All values are in USD.

Table 7: PSM (kernel matching) estimates of impacts of CA technology options in the study countries

		MSD only		RR only		CR only		MSD+RR		MSD+CR		RR+CR		MSD+RR+CR	
	Outcome	ATT	SE	ATT	SE	ATT	SE	ATT	SE	ATT	SE	ATT	SE	ATT	SE
Ethiopia	Income			52.44	99.09	60.45	106.59					-34.74	42.56		
	Income_AE			4.95	24.03	-2.14	28.78					-10.40	11.26		
Ghana	Income	202.53**	82.23			722.43*	407.42	339.95*	198.74	384.36**	197.19			320.33*	187.59
	Income_AE	84.70**	33.39			172.08*	93.18	203.41**	95.19	117.10**	59.27			-1.11	37.57
Kenya	Income			91.61	193.18	270.35	529.81					127.88**	58.64	30.30	91.48
	Income_AE			31.95	38.20	54.60	75.35					30.47	19.73	4.48	28.00
Malawi	Income	3.04	51.33	186.08	186.36	83.17*	47.76	186.75*	100.39	4.00	59.35	136.25**	56.64	42.59	84.64
	Income_AE	-7.42	18.21	93.29	86.62	25.58	17.82	64.22	41.74	-10.69	22.41	35.45*	19.32	-3.69	25.44
Mozambique	Income	37.82	104.71	180.36	128.57	-151.35***	50.67			40.54	97.88				
	Income_AE	26.22	25.69	83.51**	40.45	-31.58**	12.74			64.69	64.10				
Nigeria	Income	-231.99	191.55	77.90	307.94	-92.64	144.33					90.35	72.93	650.12	658.95
	Income_AE	-61.28	40.46	30.56	104.91	-34.70	29.33					-8.37	241.89	389.97**	178.21
Tanzania	Income	8.71	21.97	143.23	130.73	80.29	161.71	98.62	124.10	336.54***	120.53	164.85	301.05	352.15*	195.05
	Income_AE	-16.50	108.25	46.37	31.09	49.37	60.84	37.27	25.41	85.89**	37.00	79.57	74.14	125.36**	60.94
Uganda	Income			150.63	318.15	150.63	318.15					404.94***	142.37		
	Income_AE			20.61	69.76	20.61	69.76					60.39	48.16		
Zambia	Income					17.77	98.03			-187.04	141.23	-332.03***	120.91	-18.27	139.96
	Income_AE					-8.21	24.95			-56.19	42.61	-109.85***	36.40	-29.42	39.82

***, **, * denote 1%, 5%, and 10% significance level, respectively. All values are in USD.

Appendix

Table A1: Balancing tests before and after kernel matching

	Before matching			After matching		
	R^2	Mean bias	LR χ2 P-value	R^2	Mean bias	LR χ2 P-value
MSD only	0.067	13.6	0.000	0.002	2.2	1.000
RR only	0.071	15.8	0.000	0.002	2.1	1.000
CR only	0.074	16.6	0.000	0.004	4.4	0.578
MSD+RR	0.079	18.3	0.000	0.002	2.4	1.000
MSD+CR	0.247	34.2	0.000	0.014	5.1	0.913
RR+CR	0.173	26.1	0.000	0.007	4.9	0.647
MSD+RR+CR	0.317	41.4	0.000	0.023	9.5	0.587

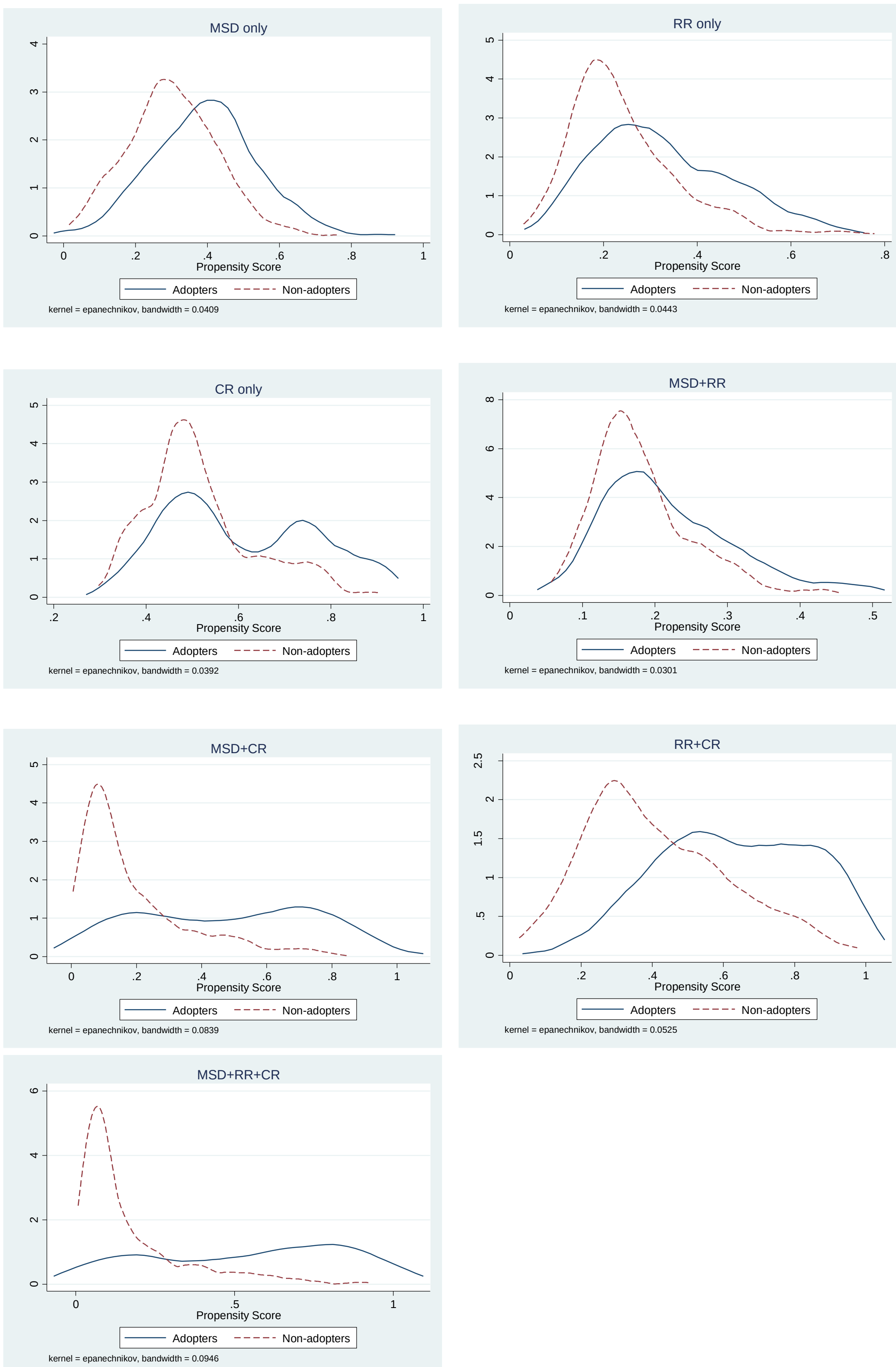

Figure A1: Kernel density distribution showing overlap between adopters of alternative CA practices and non-adopters.

Acknowledgements

This research was financially supported by the German Federal Ministry for Economic Cooperation and Development (BMZ) through the research projects "Promoting Food Security in Rural Sub-Saharan Africa: The Role of Agricultural Intensification, Social Security and Results-Oriented Approaches" and "Program of Accompanying Research for Agricultural Innovation (PARI)". This article draws on data from the Lund University led *Afrint II* project, which was funded by the Swedish International Development Cooperation Agency and the Swedish Research Foundation. The authors gratefully acknowledge the team of researchers from Sweden and the nine African countries who were involved in the *Afrint II* project.

References

Abdulai, A.N., 2016. Impact of conservation agriculture technology on household welfare in Zambia. Agricultural Economics 47, 729-741.

Andersson, J.A., D'Souza, S., 2014. From adoption claims to understanding farmers and contexts: A literature review of Conservation Agriculture (CA) adoption among smallholder farmers in southern Africa. Agriculture, Ecosystems & Environment 187, 116-132.

Andersson, J.A., Giller, K.E., 2012. On heretics and God's blanket salesmen: Contested claims for Conservation Agriculture and the politics of its promotion in African smallholder farming. In: Sumberg, J., Thompson, J. (Eds.), Contested Agronomy: Agricultural Research in a Changing World. Routledge, London, pp. 22-46.

Arslan, A., McCarthy, N., Lipper, L., Asfaw, S., Cattaneo, A., 2014. Adoption and intensity of adoption of conservation farming practices in Zambia. Agriculture, Ecosystems & Environment 187, 72-86.

Brown, B., Llewellyn, R., Nuberg, I., 2017. Global learnings to inform the local adaptation of conservation agriculture in Eastern and Southern Africa. Global Food Security. http://dx.doi.org/10.1016/j.gfs.2017.10.002.

Caliendo, M., Kopeinig, S., 2008. Some practical guidance for the implementation of propensity score matching. Journal of Economic Surveys 22, 31-72.

Corbeels, M., De Graaff, J., Ndah, T.H., Penot, E., Baudron, F., Naudin, K., ... Rusinamhodzi, L., 2014a. Understanding the impact and adoption of conservation agriculture in Africa: A multi-scale analysis. Agriculture, Ecosystems & Environment 187, 155-170.

Corbeels, M., Sakyi, R.K., Kühne R.F., Whitbread A., 2014b. Meta-analysis of crop responses to conservation agriculture in sub-Saharan Africa. CCAFS Report No. 12, Copenhagen.

Djurfeldt, G., Aryeetey, E., Isinika, A.C., (Eds.) 2011. African smallholders: Food crops, markets and policy. CABI, Wallingford.

FAO., 2017. Conservation Agriculture. Rome: FAO. www.fao.org/ag/ca. Accessed on 15 July 2017.

FAO, IFAD, UNICEF, WFP, WHO., 2017. The State of Food Security and Nutrition in the World 2017. Building resilience for peace and food security. FAO, Rome.

Foley, J.A., Ramankutty, N., Brauman, K.A., Cassidy, E.S., Gerber, J.S., Johnston, M., ... Balzer, C., 2011. Solutions for a cultivated planet. Nature 478, 337-342.

Gebremedhin, B., Swinton, S.M., 2003. Investment in soil conservation in northern Ethiopia: the role of land tenure security and public programs. Agricultural Economics 29, 69-84.

Giller, K.E., Witter,E., Corbeels, M., Tittonell, P., 2009. Conservation agriculture and smallholder farming in Africa: the heretics' view. Field Crops Research 114, 23-34.

Godfray, H.C.J., Beddington, J. R., Crute, I.R., Haddad, L., Lawrence, D., Muir, J.F, Pretty, J., Robinson, S., Thomas, S.M., Toulmin, C., 2010. Food Security: The Challenge of Feeding 9 Billion People. Science 327, 812-818.

Grabowski, P.P., Kerr, J.M., Haggblade, S., Kabwe, S., 2016. Determinants of adoption and disadoption of minimum tillage by cotton farmers in eastern Zambia. Agriculture, Ecosystems & Environment 231, 54-67.

Hobbs, P. R., Sayre, K., Gupta, R., 2008. The role of conservation agriculture in sustainable agriculture. Philosophical Transactions of the Royal Society of London B: Biological Sciences 363, 543-555.

Jarecki, M.K., Lal, R., 2003. Crop management for soil carbon sequestration. Critical Reviews in Plant Sciences 22, 471-502.

Kassam, A., Friedrich, T., Shaxson, F., Pretty, J., 2009. The spread of conservation agriculture: justification, sustainability and uptake. International Journal of Agricultural Sustainability 7, 292-320.

Knowler, D., Bradshaw, B., 2007. Farmers' adoption of conservation agriculture: A review and synthesis of recent research. Food Policy, 32(1), 25-48.

Lechner, M., 2002. Program heterogeneity and propensity score matching: An application to the evaluation of active labor market policies. The Review of Economics and Statistics 84, 205-220.

Mango, N., Siziba, S., Makate, C., 2017. The impact of adoption of conservation agriculture on smallholder farmers' food security in semi-arid zones of southern Africa. Agriculture & Food Security 6: 32, 1-8.

Mazvimavi, K., Twomlow, S., 2009. Socioeconomic and institutional factors influencing adoption of conservation farming by vulnerable households in Zimbabwe. Agricultural Systems 101, 20-29.

Ndah, H.T., Schuler, J., Uthes, S., Zander, P., Traore, K., Gama, M.S., Nyagumbo, I., Triomphe, B., Sieber, S. and Corbeels, M., 2014. Adoption potential of conservation agriculture practices in sub-Saharan Africa: results from five case studies. Environmental management, 53,620-635.

Ng'ombe, J.N., Kalinda, T.H., Tembo, G., 2017. Does adoption of conservation farming practices result in increased crop revenue? Evidence from Zambia. Agrekon 56, 205-221.

Ngoma, H., Mason, N.M., Sitko, N.J., 2015. Does minimum tillage with planting basins or ripping raise maize yields? Meso-panel data evidence from Zambia. Agriculture, Ecosystems & Environment 212, 21-29.

Nkala, P., Mango, N., Zikhali, P., 2011. Conservation agriculture and livelihoods of smallholder farmers in Central Mozambique. Journal of Sustainable Agriculture 35, 757-779.

Pittelkow, C. M., Liang, X., Linquist, B.A., Van Groenigen, K.J., Lee, J., Lundy, M. E., van Gestel, N., Six, J., Venterea, R. T., van Kessel, C., 2015. Productivity limits and potentials of the principles of conservation agriculture. Nature 517, 365-368.

StataCorp. 2013. Stata: Release 13. Statistical Software. College Station, StataCorp LP, Texas

Teklewold, H., Kassie, M., Shiferaw, B., Köhlin, G., 2013. Cropping system diversification, conservation tillage and modern seed adoption in Ethiopia: Impacts on household income, agrochemical use and demand for labor. Ecological Economics 93, 85-93.

The Montpellier Panel., 2013. Sustainable Intensification: A New Paradigm for African Agriculture. Agriculture for Impact, London.

Tsegaye, W., LaRovere, R., Mwabu, G., Kassie, G.T., 2016. Adoption and farm-level impact of conservation agriculture in Central Ethiopia. Environment, Development and Sustainability, 1-17.

Tittonell, P., Klerkx, L., Baudron, F., Felix, G.F., Ruggia, A., van Apeldoorn, D. Dogliotti, S., Mapfumo, P., Rossing, W.A.H., 2016. Ecological intensification: local innovations to address global challenges. In: Lichtfouse, E. (Eds.), Sustainable Agriculture Reviews 19.

van Ittersum, M. K., Van Bussel, L.G., Wolf, J., Grassini, P., Van Wart, J., Guilpart, N., ... Yang, H., 2016. Can sub-Saharan Africa feed itself? Proceedings of the National Academy of Sciences 113, 14964-14969.

Wainaina, P., Tongruksawattana, S., Qaim, M., 2017. Synergies between different types of agricultural technologies in the Kenyan small farm sector. The Journal of Development Studies doi: 10.1080/00220388.2017.1342818.

Wooldridge, J.M., 2010. Econometric analysis of cross section and panel data (2nd Ed.). MIT Press, Cambridge, MA.